Building and Environment 155 (2019) 350–359

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Rethinking HVAC temperature setpoints in commercial buildings: The potential for zero-cost energy savings and comfort improvement in different climates

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ARTICLE INFO

Keywords:
HVAC
Thermostat setpoints
Human-based retrofits
Energy savings
Thermal comfort
Multi-objective optimization

ABSTRACT

Heating, Ventilation, and Air Conditioning (HVAC) systems are responsible for a significant share of the energy consumed in commercial buildings. While energy system retrofits have been found to reduce buildings' carbon footprint substantially, these measures are often hindered by financial, regulatory or design constraints. Recent research sheds light on energy management approaches to energy conservation such as energy-efficient settings of HVAC temperature setpoints. While existing case studies confirm the significant energy saving potential of efficient HVAC operation, there is scarcity of studies quantifying energy savings from optimal HVAC temperature setpoints comprehensively, while controlling for important factors, such as guaranteeing tenant thermal comfort levels and the impact of different climate conditions on the results. In this work, we apply simulation-based multi-objective optimization to fine-tune heating and cooling setpoints of large "typical" office buildings with respect to energy consumption and occupant thermal comfort. We apply the framework in seven climate zones across the US in an effort to examine spatial variations in the energy savings potential due to different climate conditions and propose targeted energy-saving strategies and policies. We show that locations with mild climates, such as San Francisco, CA, can realize up to 60% of annual HVAC-related energy savings without compromising the occupants' thermal comfort. This untapped potential to simultaneously improve building performance and occupants' comfort drives the discussion on revisiting HVAC setpoint configuration standards in commercial buildings, either as part of individual building retrofit planning or as part of energy policy regulations.

1. Introduction

Energy security, natural resources depletion, and global warming are pushing developed countries to reduce the energy demand and carbon footprint of their various sectors. In the United States (U.S.), commercial buildings account for approximately 20% of national energy consumption and greenhouse gas emissions, and are often identified as the sector with the highest potential for large-scale energy savings [1,2]. More than 40% of that energy demand is typically attributed to the buildings' Heating, Ventilation, and Air Conditioning (HVAC) system [2,3], increasing the need for retrofit measures to reduce their energy intensity. Specifically, there are two primary types of retrofits described in academic literature: technical retrofits and human-based retrofits (i.e. operation-focused interventions).

Technical retrofits include replacing a building's physical components with more efficient ones (e.g. wall or roof insulation, high performance windows, efficient chillers). The potential of technical retrofits has been extensively studied and remains an active research field [4,5,6,7]; Kaklauskas et al., 2005; Rey 2004). Examples can be found where the effect of individual retrofits on building performance was assessed [8,9,10], or the retrofit strategy was studied in a comprehensive manner as part of an optimization process [4,5,6,11,12,13]. Despite their advantages, such measures often involve socio-technical or economic complexities that might hinder their adoption by building owners/tenants. To begin with, technical retrofits (and HVAC-related measures in particular) come with high upfront capital costs, which could act as a barrier for stakeholders even if the investment is cost-effective in the long term. Local market constraints and building

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https://doi.org/10.1016/j.buildenv.2019.03.062
Received 11 December 2018; Received in revised form 10 March 2019; Accepted 30 March 2019
Available online 04 April 2019

ownership type might also affect the retrofit decision [14]. Moreover, newly constructed buildings must typically fulfill specific energy codes, guarantying certain levels of efficient building design [15]. In such cases, further retrofitting can become cost-ineffective from an investment point of view. Finally, technical retrofits often require modifications to existing buildings' design, which can be challenging especially in old and historic buildings.

On the other hand, the term human-based retrofits [15] refers to actions that building occupants or facility managers can take to improve building energy performance through more efficient systems operation. Examples of such actions include, adjusting the temperature setpoints of the HVAC system, reducing lighting and equipment usage, or opening windows for natural ventilation, to name a few. In general, human-based retrofits come with little to no implementation costs. Recent studies also demonstrate a significant potential for energy savings, with documented savings up to 20% of the building's total energy consumption [17,18,19]. Among the different actions that can be taken by occupants and facility managers to reduce energy consumption, adjusting thermostat setpoints to minimize cooling or heating loads has particularly shown a significant impact on building performance [20,21,22,23,24].

Despite the growing interest in the literature, research on human actions in general, and HVAC thermostat setpoints in particular, has important limitations that motivate the need for the current study. First, thermal comfort, an important building performance metric, is often not considered in energy conservation studies, overlooking potential tradeoffs between energy savings and the comfort and wellbeing of occupants [5,20]. Second, studies that consider these metrics often evaluate them individually with pre-defined and pre-evaluated sets of solutions; they rarely propose methods to optimize them simultaneously [25,26,63]. Finally, promising research efforts aimed to tackle the above limitations by optimizing multiple metrics simultaneously [17,27,28,29,30]. However, the majority of these studies are typically limited to small scale experiments and do not cover different climatological contexts [20,25,63]. Consequently, it is challenging to scale-up their results to reflect on the performance of a large build stock (e.g., US office buildings) and guide energy-saving strategies and policies that do not compromise the indoor environmental conditions of building users.

The goal of this study is to assess the energy-saving potential of large office buildings in various climate zones through efficient HVAC heating and cooling setpoint adjustment, accounting for the trade-offs between energy consumption and thermal comfort. To do so, we apply a simulation-based multi-objective optimization framework based on a genetic algorithm on large “typical” office building models in seven distinct US climate zones. As detailed later, we find a significant potential for HVAC energy savings, reaching up to 60% under certain climate conditions. The findings motivate the need to revisit building energy standards, which lack specific guidelines on recommended climate-sensitive set points ranges that can help achieve a comfortable and energy-efficient built environment.

The paper is structured as follows. In Section 2 we review recent studies discussing the influence of HVAC operation on building performance, as well as applications of multi-objective optimization on the built environment. Section 3 discusses the methodological details of our multi-objective optimization approach. In Section 4, we present the optimal solutions for each of the seven climate zones, and discuss their implications as well as existing limitations. Finally, Section 5 concludes the paper by summarizing the key findings and proposing ideas for future work.

2. Literature review

A growing number of studies show that the way people use and control building systems highly impacts energy consumption [31,32]. Even in new or retrofitted energy efficient buildings, inefficient operation patterns by occupants or facility managers can lead to excessive energy consumption levels [33,34]. As a result, while the traditional approach to energy conservation has been mostly focused on improving building design, there is a growing trend to focus and improve how occupants and facility managers operate various systems. Among the different actions that can be taken by occupants to save energy, adjusting thermostat setpoints to save on cooling or heating loads has been shown to have the highest potential [35]. Additionally, such intervention comes with little to no direct financial cost and its implementation is not limited by architectural constraints [20,21,22,23,24].

Intra-building occupant behavior and energy efficiency awareness is gaining momentum as a nudging mechanism [31,36]. Several campaigns have been launched worldwide targeting energy savings through the adjustment of thermostat setpoints [37,38,39]. In 2005, the Japanese government launched the “CoolBiz” campaign [37], advocating a minimum cooling setpoint of 28 °C in public office buildings. Whilst stakeholders claimed the success of the policy, complementary studies questioned the policy's adverse effect on thermal comfort and productivity [40]. Focusing on HVAC system operation, various studies examine the impact of setpoints and deadband widening (i.e. thermostat setpoint range) on energy end use [20,25,41,63]. Lakeridou et al. [63] conducted a field study to determine whether a 2 °C increase (from 22 to 24 °C) in office buildings in the United Kingdom would affect thermal comfort. The results show that this increase appears not to cause substantial discomfort to the group under study. Despite the interesting findings of such studies, the tested scenarios are pre-defined and do not cover a wide search space. Consequently, the proposed setpoints can be considered good, but not necessarily optimal in terms of simultaneously maximizing energy savings and thermal comfort, which are multiple objectives that may conflict with each other.

Multi-objective optimization (MOO) is a method that can be used to tackle such a problem. Due to the competing nature of the objectives, there is typically no single solution that simultaneously optimizes all of them, hence the need for a set of non-dominated (Pareto optimal) solutions. A solution is called Pareto optimal when none of the objectives can be further improved without degrading some of the other objective functions [42]. MOO algorithms have been applied in the context of building energy studies to identify the set of optimal energy conservation measures, subject to objectives such as energy consumption, implementation cost, or life-cycle cost. For instance Ref. [13], were among the first to introduce MOO in existing building retrofitting. They provided a simplistic representation of a building's components and applied three different MOO techniques to identify the trade-offs between energy consumption and retrofit cost. Their findings set the ground for in-depth research in the field, such as the work of [11]; who proposed a retrofit optimization framework using artificial neural network and genetic algorithm. They demonstrated the practicability of their approach using a case study on an existing school building, studying the interaction between energy consumption, retrofit capital cost and thermal discomfort hours. In general, while technical retrofits are increasingly studied through optimization problems, human-based interventions are less commonly considered [15,18].

Another important factor to consider in the literature on human-based retrofits, in particular HVAC settings, is the ability to generalize the results to guide decision-making (e.g. building standard revisions or energy policy). Our review indicates that a majority of studies lacks generalizability, meaning that they focus on individual building case studies and do not account for the effect of different environmental conditions on the results. Put differently, an optimal HVAC setpoint strategy in hot climates might not necessarily be adequate for colder climates, and vice-versa. Such knowledge is even missing from commonly used building standards such ASHRAE 90.1 and 55 standards [43,44], which do not currently provide climate-sensitive guidelines or recommended ranges for ideal HVAC set settings. Few studies have expanded their scope of HVAC operation analysis to cover different climate conditions. For instance Ref. [45], simulated a generic small

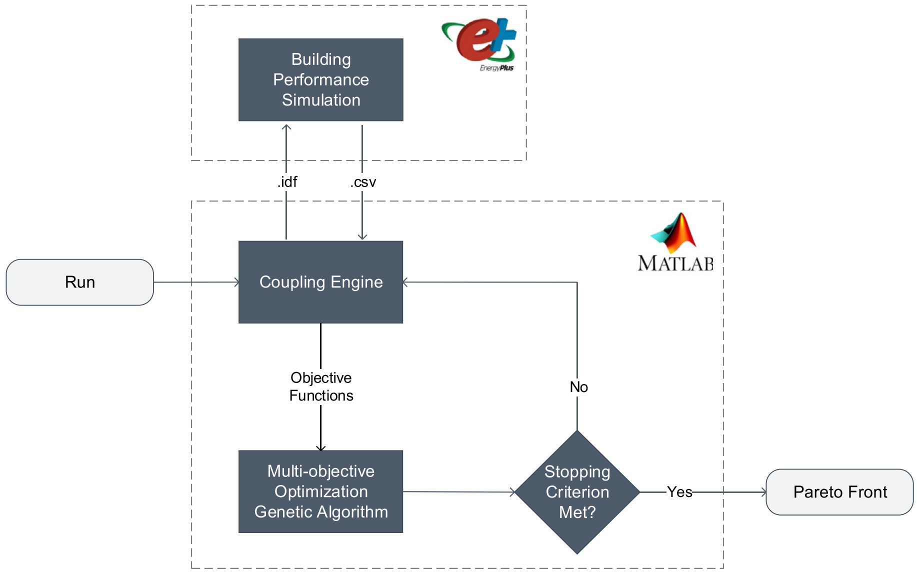

Fig. 1. Proposed optimization framework.

office building with two different HVAC systems and applied this to five climate zones in the US. They found that efficient thermostat control can result in different energy savings in different climates, 22–50% for electricity and 47–87% for natural gas [46]. conducted a similar analysis of three US climate zones and tested various thermostat control strategies. Energy savings in the range of 18–51% were observed. Finally, the authors of [47] developed two algorithms to determine the optimal HVAC set points and cycling rates of roof-top units in different climate zones and found that savings can reach 20% for some of the studied buildings. In general, the above studies are mostly focused on energy conservation alone, further motivating the need for the current work that proposes an applied framework to optimize HVAC settings given two objectives: energy reduction and thermal comfort improvement.

3. Methodology

3.1. Overview

The optimization framework used in this study in shown in Fig. 1 and further detailed in the upcoming sections. The first step consists of developing the building performance simulation (BPS) model(s) for the building(s) under study. In parallel, we implement a MOO algorithm to evaluate the objective functions of the study until a stopping criterion is met. Upon convergence, the MOO algorithm outputs a Pareto front, including the non-dominated solutions for all problem objectives. To enable the connection between the BPS software and the MOO algorithm, we develop a coupling scheme, facilitating a simulation-based evaluation of the objective functions, as well as the tuning of parameters in the BPS model according to the values of the problem's decision variables in each iteration. It is important to note that the proposed methodology builds on previous work of the authors [27] where the original proof-of-concept of the coupling and optimization approach was illustrated and validated on a single building.

3.2. Building performance simulation model

BPS is a widely used technique among architects and building performance experts to predict a building's energy consumption, given a set of detailed physical characteristics, operation schedules and outdoor weather conditions. Among the different commercial BPS tools available, EnergyPlus is used in this study given its robust and validated modeling and analysis capabilities [16,48]. Additionally, its text-based inputs and outputs facilitate the integration with mathematical tools and programing languages, which makes it a commonly used tool in simulation-based optimization research [49]. For existing buildings, the development of BPS is typically followed by a calibration process that ensures that the model's monthly energy predictions are in line with actual energy consumption levels monitored from the building [50]. Alternatively, existing energy models can be used such as the commercial prototype buildings developed by the US DOE [51]. These models are commonly used for research applications and cover “typical” or “archetype” commercial buildings in the US of that vary according to different building type, size, age, and location (i.e., climate zones).

3.3. Coupling scheme

The purpose of the coupling scheme is to act as a connector between the BPS software (i.e., EnergyPlus) and a platform that supports optimization algorithms (i.e., MATLAB). EnergyPlus models typically use text-based inputs (.idf files) and output the simulation results in comma delimited workbooks (.csv files). The coupling scheme loads the.idf file as a data structure, where each class refers to a simulation parameter and each field refers to a hyper-parameter associated with the class. For instance, if a given class is “Construction”, its fields would include information such as the element's name and the layers that compose it. Next, the simulation is then triggered in the MATLAB environment. Once the simulation is completed, the MOO algorithm evaluates the objectives of the optimization problem. While the stopping criterion is not met, the algorithm returns a new set of decision variables to be evaluated. The decision variables' values then act as new inputs in the BPS model, a new.idf file is created, and a new simulation is triggered. The process is repeated until the algorithm converges to a set of non-dominated solutions.

3.4. Multi-objective optimization algorithm

3.4.1. Overview

The MOO algorithm we use in this work is a controlled elitist genetic algorithm (GA) (variant of NSGA-II) [42], implemented in MATLAB's global optimization toolbox [52]. The simulation-based evaluation of the objective functions makes the optimization problem nonlinear, discontinuous and non-differentiable. Therefore, heuristic approaches, such as GA, are commonly used tools in similar optimization problems [49]. GA is based on a natural selection process, mimicking the natural biological evolution of living organisms [53]. As such, GA exploits the search space in an intelligent manner to solve optimization problems. In each iteration (generation) of the algorithm, the fittest individuals dominate the weaker ones and progress. Eventually, the algorithm converges to the fittest individual that represents the optimal solution. In GA, the individuals of a population are encoded as solutions (chromosomes) and each variable string consists of a set of decision variables (genes), analogous to the structures encountered in organisms' DNA and corresponding to a unique position in the search space.

It is critical for the initial population of S individuals to belong in the feasible region of the problem, otherwise computationally expensive techniques need to be employed [52]. This is not a concern for the current application since the constraints are defined exclusively by the upper and lower bounds of the decision variables. Therefore, it is a common process to follow an almost random process in the generation of the initial population to enhance diversity among individuals and cover a wide range of the search space [54].

Initially, a random population P_0 is created and sorted based on non-domination. Following, a new population is created, based on the genetic operators, namely (i) selection, (ii) crossover, and (iii) mutation. The fittest individuals of each generation (parents) are chosen based on a tournament selection. Then, the parents either progress in the next generation (*EliteCount*), or crossover to form new solutions (children) with a certain probability ($P_{crossover}$). Additionally, some of the parents' characteristics are changed to produce a mutated child with a mutation probability ($P_{mutation}$). The following populations are ranked based on both non-domination and the crowding distance of each individual. The crowding distance is a measure of how far an individual is located with respect to the objective functions and is used to enhance the diversity among the solutions. More detailed explanation of the NSGA-II algorithm is beyond the scope of this work. The authors refer interested readers to the work of [55].

For the implementation of the current framework, the genetic operator values are specified as follows: $EliteCount = 2$, $P_{crossover} = 0.8$ and $P_{mutation} = 0.01$ [52]. Moreover, two stopping criteria are defined: (i) when the algorithm exceeds 50 generations and (ii) when the average relative change in the fitness function falls below the default tolerance of 1e-6. The pseudo code provided in Fig. 2 summarizes the NSGA-II process.

3.4.2. Decision variables

The decision variables of the problem represent the set of alternative measures considered in the optimization of the HVAC system operation. More specifically, four variables are considered, covering both heating and cooling setpoints for occupied and unoccupied hours. All variables are assumed continuous in order to add more granularity in the analysis and broaden the problem's search space. Table 1 summarizes the problem's decision variables with their corresponding lower and upper bounds. The chosen ranges fall within the acceptable temperature values defined by ASHRAE 90.1 and 55 standards [43,44].

3.4.3. Objective functions

As discussed previously, in this work, we assess the trade-offs between energy consumption and thermal comfort for commercial buildings in various US climate zones.

We obtain all HVAC-related energy consumption from the EnergyPlus simulation. We estimate the heating and cooling requirements for a yearly simulation in order to capture the seasonal effect on energy consumption. Following, we aggregate the estimates in the annual total energy consumption, expressed in megawatt-hours (MWh). The energy requirements for lighting, equipment, and domestic hot water are not considered in the calculations, under the assumption that they are not significantly affected by the HVAC system's operation.

Thermal comfort in the built environment can be mainly assessed by two metrics: (a) the Predicted Mean Vote (PMV), and (b) the Predicted Percentage of Dissatisfied people (PPD), both based on Fanger's model [56] and detailed in ISO 7730:2005 [57]. PMV takes both negative and positive values, ranging from -3 (too cold) to $+3$ (too hot), whereas PPD is expressed as a percentage. Since the PPD index's values are always positive, it is considered as a more suitable metric for optimization purposes and we use in the problem formulation. Specifically, we output the PPD for all hours that each zone is occupied by at least one person. We then average the values for all occupied hours for all zones to obtain the average annual PPD.

3.4.4. Problem formulation

After the BPS model is developed and the decision variables and objective functions are defined, we formulate the MOO problem and solve it with MATLAB's multi-objective GA solver. The output of this process is a set of non-dominated solutions for all two objectives. The MOO problem formulation is summarized in the following Eq. (1):

$t \leftarrow 0$

Initialize population $P_t = \{X_i^{(t)}\}_{i=1,\dots,S}$

Evaluate fitness of $P_t = \{X_i^{(t)}\}_{i=1,\dots,S}$ based on rank

WHILE stopping criterion is not met **DO**

> $t \leftarrow t + 1$
>
> Select parents from P_{t-1}
>
> Generate $P_t = \{X_i^{(t)}\}_{i=1,\dots,S}$ using genetic operators (i.e. crossover, mutation)
>
> Evaluate fitness of $P_t = \{X_i^{(t)}\}_{i=1,\dots,S}$ based on rank and crowding distance

END WHILE

Return set of non-dominated solutions (Pareto front)

Fig. 2. MOO GA pseudo code.

Table 1
Decision variables.

Variable	Description	Lower bound	Upper bound
x_{occ_cool}	Cooling temperature setpoint for occupied hours	22 °C	27 °C
x_{occ_heat}	Heating temperature setpoint for occupied hours	17 °C	22 °C
x_{unocc_cool}	Cooling temperature setpoint for unoccupied hours	27 °C	30 °C
x_{unocc_heat}	Heating temperature setpoint for unoccupied hours	14 °C	17 °C

$$min\ Z_1(X) = EnergyConsumption(X)$$

$$\min Z_2(X) = PPD(X)$$

subject to,

$$22 \le x_{occ\_cool} \le 27^oC$$

$$17 \le x_{occ_{heat}} < 22^oC$$

$$27 < x_{unocc\_cool} \le 30^oC$$

$$14 \le x_{unocc\_heat} < 17^oC$$

$$X = \{x_{occ\_cool}, x_{occ\_heat}, x_{unocc\_cool}, x_{unocc\_heat}\}$$

where Z_1 corresponds to the building's annual heating and cooling energy consumption in *MWh* and, Z_2 is the average annual PPD (%) from all building zones. Vector *X* contains the set of decision variables to be evaluated by the multi-objective GA.

4. Case studies and discussion

The presented methodology is applied on 'prototype' large offices located in seven different climate zones across the US [51]. We select the locations for our case studies to cover a diverse mix of climate zones to determine whether optimal HVAC settings differ for buildings subjected to different weather conditions. Fig. 3 shows the breakdown of the US climate zones based on temperature (1: 'very hot' to 7: 'very cold') and humidity levels (A: 'moist', B: 'dry', C: 'marine'). We apply the optimization framework in the following seven locations: Miami, FL (1A), Phoenix, AZ (2B), San Francisco, CA (3C), Baltimore, MD (4A), Boulder, CO (5B), Minneapolis, MN (6A), Duluth, MN (7A).

4.1. Building model description

The BPS models for the buildings analyzed in this work are obtained from the list of commercial prototype buildings, developed by the US DOE [51]. The buildings modeled for this study are constructed after 1980, are 12 floors high, and their gross floor area is 46,320 m^2. The proportion of the windows to the buildings overall surface is 38%. Heating loads are served by gas boiler, whereas the cooling demand by two water-cooled chillers. As for the occupancy schedules, the buildings are considered occupied during weekdays from 6:00 a.m. to 10:00 p.m., on Saturdays from 9:00 a.m. to 5:00 p.m., and on Sundays/holidays the buildings are considered unoccupied. Building envelope, roof, wall and window u-values vary among different locations. The baseline HVAC operation setpoint conditions are non-variable in all locations with the cooling setpoint being 24 °C for the occupied, and 26.7 °C for the unoccupied hours, and the heating setpoint 21 °C and 15.6 °C for the occupied and unoccupied hours, respectively. For more detailed information on the models' features we refer interested readers to the work of [51].

4.2. Multi-objective optimization results

In this section, we present the optimization results for the seven climate zones. Since thermal comfort can be in conflict with energy conservation, no single solution can be obtained, as discussed in the Methodology section. Thus, a set of non-dominated solutions (also known as Pareto fronts) is obtained for each building under study. In Fig. 4 we show the Pareto fronts for the seven different buildings. The filled black star represents the baseline HVAC energy loads and average thermal comfort levels, whereas the blue stars represent the non-dominated solutions. Interestingly, we notice that the potential for energy savings varies significantly with climate conditions. Specifically,

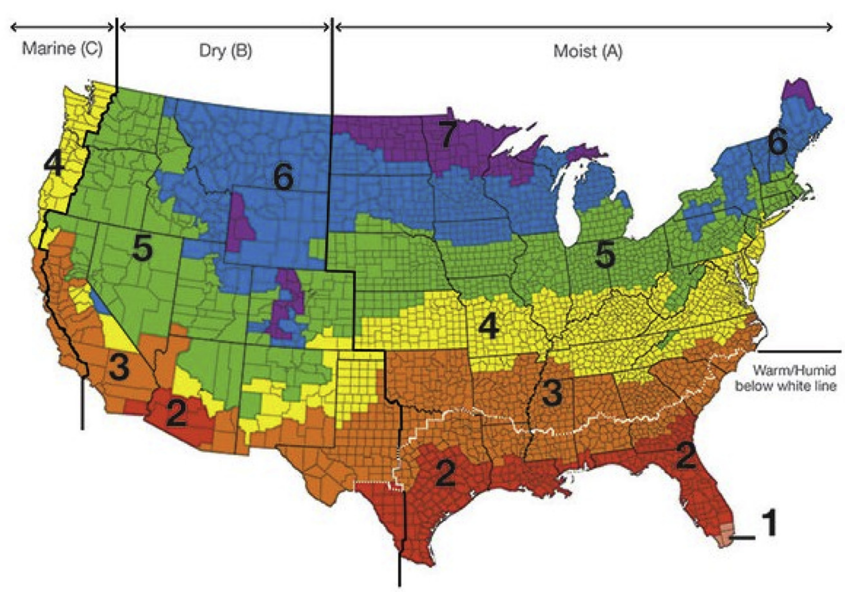

Fig. 3. US climate zone classification map [62].

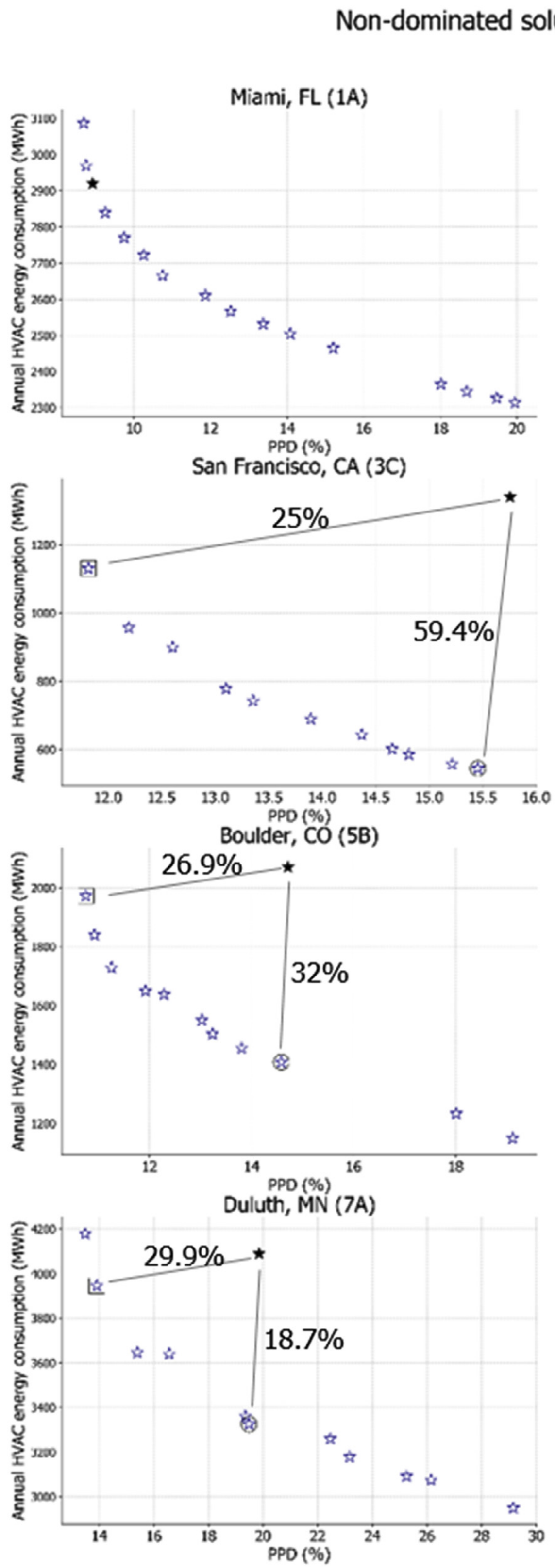

Fig. 4. Pareto fronts for different climate zones. The circled solution represents the solution that minimizes energy consumption without compromising PPD according to its baseline levels (black star), whereas the squared solution is the one that minimizes thermal dissatisfaction with no additional burden on energy consumption. The percentages show the difference between the aforementioned solutions and the baseline levels for energy consumption and PPD respectively.

in hot areas, such as Miami and Arizona, we notice that the Pareto front is placed close to (or on) the baseline conditions, meaning that the potential for energy saving is trivial. Areas with more balanced climates, on the other hand, such as Baltimore, Boulder and San Francisco, show the greatest potential for setpoint tuning. In the case of San Francisco, particularly, we notice a quite interesting finding; all the

Table 2
Optimal HVAC setpoints for energy consumption optimization without compromising thermal comfort.

City	Cooling Occupied Setpoint (°C)	Heating Occupied Setpoint (°C)	Cooling Unoccupied Setpoint (°C)	Heating Unoccupied Setpoint (°C)	Percentage Energy Savings
Miami, FL	–	–	–	–	–
Phoenix, AZ	24.3	21	28.5	15.2	1.20%
San Francisco, CA	26.9	17.5	27.8	14.7	59.38%
Baltimore, MD	26.2	20.5	28.8	14.6	21.89%
Boulder, CO	26.6	19.9	29.3	14.6	31.97%
Minneapolis, MN	25.5	20.3	27.8	16.2	11.53%
Duluth, MN	26.4	20.1	28.3	14.1	18.70%

Table 3
Optimal HVAC setpoints for thermal comfort optimization without compromising energy consumption.

City	Cooling Occupied Setpoint (°C)	Heating Occupied Setpoint (°C)	Cooling Unoccupied Setpoint (°C)	Heating Unoccupied Setpoint (°C)	Percentage Thermal Comfort Improvement
Miami, FL	–	–	–	–	–
Phoenix, AZ	24.3	21	28.5	15.2	0.91%
San Francisco, CA	26.2	22	29	15.2	24.99%
Baltimore, MD	25.4	21.8	28.7	15.1	20.87%
Boulder, CO	25.9	21.9	28.8	16.1	26.91%
Minneapolis, MN	25.6	21.9	28	15.2	26.94%
Duluth, MN	26.4	21.9	28	15.7	29.87%

non-dominated solutions improve both energy consumption and thermal comfort compared to the baseline conditions. Finally, for colder regions we observe a moderate potential for energy savings as well.

The circled and squared solutions are the setpoint configurations that minimize energy consumption and thermal discomfort, respectively, without compromising the competing objective's baseline condition. These solutions allow to ask the question "how much we can improve energy consumption, while not going above the pre-defined thermal dissatisfaction levels?“, and vice versa. Tables 2 and 3 detail these solutions for each climate zone. As expected, San Francisco demonstrates the highest elasticity in terms of setpoint configuration, with cooling setpoints reaching 27 °C and heating setpoints 17.5 °C. This results in significant energy savings of up to 60% of the annual HVAC energy consumption. Boulder follows with more than 30% energy saving potential, whereas the potential is significant in Baltimore and Duluth, as well (22 and 19%). Minneapolis shows moderate energy saving opportunities, and finally Miami and Phoenix cannot reduce their HVAC loads without compromising occupant thermal satisfaction significantly.

In Table 3, we see that the potential for thermal comfort level improvement increases from warmer to colder climates. Again, PPD cannot be reduced in Miami and Phoenix, whereas Duluth and Minneapolis show the highest potential for improvement (up to 30%). A consistent pattern occurs in all case studies that improved thermal comfort by more than 20%; the corresponding solutions show an increase in the heating setpoint by 1 °C, which leads to less dissatisfaction hours during the winter. The energy burden associated with the heating setpoint change is compensated by increased setpoints during the cooling season. Interactions between decision variables and objective functions, such as the ones discussed here, are fully captured by the proposed optimization framework, further validating the need for its use in related applications.

In Fig. 5, we present a more granular evaluation of the PPD values for the optimal HVAC settings using scatterplots of their hourly values over a period of one year. The left part of the figure illustrates the hourly PPD values for the HVAC setting of Table 2, which maximize energy conservation without compromising thermal comfort. The right side of the figure represents the result for the scenarios of Table 3, which maximize thermal conform without compromising energy consumption. The mean annual PPD values and the baseline value are also shown and represented using horizontal solid and dotted lines, respectively. Two main observations can be drawn from the results. First, while the mean annual PPD levels are similar or lower than the baseline levels, the scatter plots clearly indicate a high number of hours every year where PPD values exceed the maximum recommended 10% threshold for buildings. In other words, while the proposed HVAC settings significantly improve mean comfort levels over the year, they are still not ideal given the outliers observed in the hourly data. This finding motivates the need to consider more dynamic and adaptive HVAC set point strategies that continually adapt and update based on indoor building conditions and direct feedback from the occupants. The second main observation from Fig. 5 is that high PPD levels are more frequently observed in the summer months, particularly the beginning of the season (i.e., May) and, in some cases, its end (i.e., October). A closer look at the assumptions of the DOE prototype models used in the current study attributes this trend to how the models account for the clothing levels of occupants. More specifically, the models are designed to switch from "winter" clothing levels of 1 Clo to "Summer" levels of 0.5 Clo on May 1st, and then switch back to 1 Clo on October 1st. This finding highlights a limitation in the existing models used, which assume discrete changes in occupants' clothing levels without taking into consideration the actual indoor environmental conditions nor how those affect their comfort. In practice, building users who are uncomfortable with thermal conditions take measure to try to minimize their discomfort (e.g., opening a window, adjusting HVAC setpoints, or adjusting clothing levels). Therefore, further research on adaptive building-occupant interaction is needed to be understand the dynamics guiding occupant behavior and better account for them in the modeling process.

4.3. Discussion

Our work presents substantial evidence to reconsider HVAC operational setpoints. Current standards suggest uniform HVAC setpoints [51,58], neglecting climatological characteristics and, consequently, leading to sub-optimal HVAC operation. We show that with proper tuning, up to 60% HVAC energy reductions can be achieved without compromising occupant thermal comfort levels. Practically speaking, in areas where weather averages range between 10 and 20 °C, such as San Francisco, configuring setpoints at 24 °C (cooling) and 21 °C (heating) is a waste of both energy and money. HVAC operation can, and should, also target occupants' thermal comfort. More conservative heating and

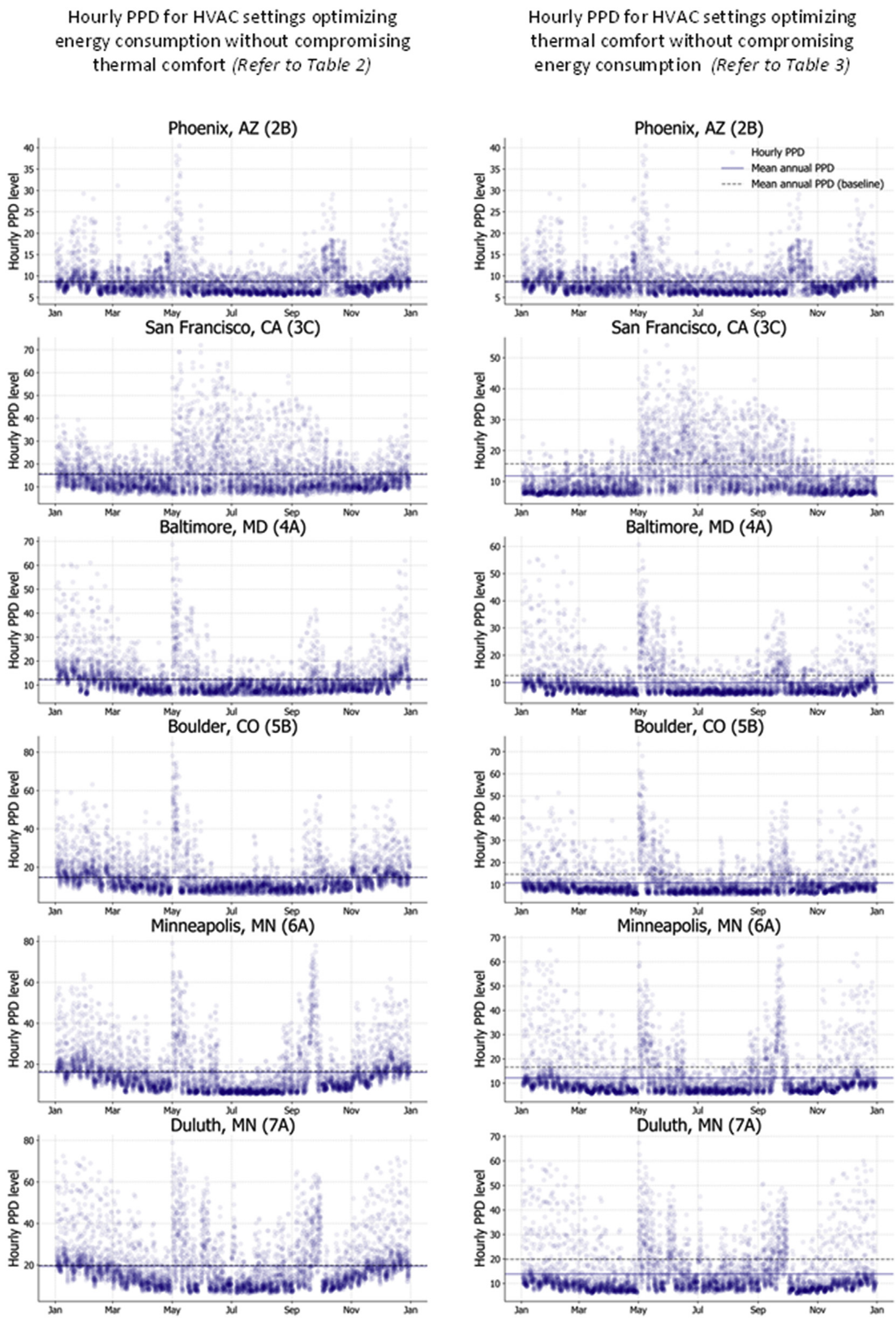

Fig. 5. Hourly PPD of optimal solutions.

more relaxed cooling setpoints can yield up to 30% indoor thermal comfort improvement in regions with balanced and cold climates. Poor thermal comfort in commercial buildings has been associated with indirect costs arising from decreased productivity [59,60].

As the effects of anthropogenic climate change become increasingly evident, energy efficiency solutions should be adopted in both small and large scales. Our approach can be applied in different scales; in individual buildings the set of non-dominated solutions can be identified and stakeholders can decide on the trade-offs between energy savings and thermal comfort. Additionally, the findings of this work can support energy policy and regulations on a large-scale and serve as a basis to revisit existing standards, transitioning towards more contextualized and quantitative HVAC operational guidelines. On the policy making frontier, similar to Japan's "CoolBiz" campaign discussed in previous section, similar policies can be introduced in the US, reinforced by scientific results that demonstrate minimal risk to compromising thermal comfort. Moreover, with upfront cost being a major barrier to energy retrofit decision [14], zero-cost retrofits can be promising alternatives to nudge building owners and managers and enable energy efficiency market transformation. Finally, the benefits of setpoint adjustment go beyond energy savings and thermal comfort improvement. As discussed by Yang et al. (2014), a relaxed range of acceptable comfort temperatures would decrease not only building energy consumption, but also peak electricity demand. This could reduce the need for new power plants and the use of “peaker” plants during periods of high demand, and allow utilities to better manage loads.

Nevertheless, the method and findings proposed in this work come with certain limitations. First, although the DOE building reference models used in the optimization framework have been extensively used for research purposes, they are only a representation of actual conditions as confirmed by the current modeling of clothing levels as static and non-adaptive behaviors. The simplistic assumptions commonly found in building energy models are believed to contribute to the common deviation of their estimates from data collected from actual buildings [61]. Second, thermal comfort level quantification is a challenge that current modeling approaches address in a rather coarse way. Indexes such as PPD, although widely adopted, are outdated and static. Recent research criticizes existing thermal comfort standards and leverages the Internet of Things to develop personalized comfort models [62]. Based on the two aforementioned points, as future work, we plan to validate our findings via field experiments in existing commercial buildings.

5. Conclusion

There is growing need to improve the built environment holistically while accounting for how building performance and occupant-related metrics, such as thermal comfort, interact and affect each other. In this work, we present an application of a multi-objective optimization framework to optimize the HVAC cooling and heating setpoints, with respect to energy consumption and occupant thermal comfort. We applied the approach on typical large office buildings in seven different climate zones in the US and quantified the potential for zero-cost human-based retrofits in each zone. This helped address the limitations of existing studies in the literature, which (1) only focused on energy conservation overlooking thermal comfort implications, (2) limited their analysis to pre-defined solutions as opposed to optimized ones, and/or (3) focused on single or few climate zones, hence leaving the influence of weather conditions on the optimal HVAC strategies unexplored. Such knowledge is essential to devise effective strategies that improve the performance of large numbers of buildings.

We found that generic thermostat setpoint settings, such as the ones used in the DOE prototype models, provide sub-optimal results in terms of energy saving and thermal comfort for moderate to cold climate zones. In particular, in regions with moderate climate there is a potential to reduce HVAC-related loads up to 60% without compromising occupant thermal comfort levels, whereas in regions where cooling loads are dominant the energy saving potential is minimal. Our methods and findings are of direct relevance to energy management practice, not only for energy efficient building design and retrofitting, but also for policy-making and data-driven performance regulations. While HVAC operation standards are uniform across different regions, here we showed that the climatological conditions of the local environment significantly impact energy saving opportunities, and this should be accounted for in future energy policy. In particular, building energy codes can provide recommended thermostat settings that are weather-dependent to ensure operation patterns that do not compromise comfort nor energy efficiency levels in buildings, which are key requirements for increasing the sustainable performance of the building sector. Finally, we reflect on the adequacy of current energy modeling tools in representing adaptive occupant behavior, highlighting the need to better account for building-occupant interactions as an important step to improve modeling predictions and guide the design of more sustainable and user-centric built environments.

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